Appl Water Sci (2017) 7:1761–1772
DOI 10.1007/s13201-015-0349-0

ORIGINAL ARTICLE

Use of artificial neural networks for electrical conductivity modeling in Asi River

Mohammad Ali Ghorbani[1] · Mohammad Taghi Aalami[2] · Leila Naghipour[2]

Received: 4 March 2015 / Accepted: 5 October 2015 / Published online: 24 October 2015

Abstract This study aims to model monthly electrical conductivity (EC) values in the Asi River using artificial neural networks (ANNs) to evaluate water quality conditions using pH, temperature, water discharge, sodium, sum of calcium and magnesium concentrations. The results are compared using multiple linear regression (MLR). Recorded data are available at a gauging site in Antakya, Turkey, for the period from 1984 to 2008. Comparing the modeled values by ANNs with the experimental data indicates that neural network model with seven neurons in hidden layer provides accurate results ($R^2 = 0.968$, RMSE = 46.927 µS/cm, MAE = 32.462 µS/cm and MRSE = 0.0029 for the training data and $R^2 = 0.965$, RMSE = 50.810 µS/cm, MAE = 37.495 µS/cm and MRSE = 0.0024 for the testing data). The Garson method of the connection weights of the network was used to study the relative % contribution of each of the input variables. It was found that the sum of calcium and magnesium concentration and temperature had the most effect on the predicted EC. The results indicate that two proposed models were able to approximate the EC parameter reasonably well; however, the ANN was found to perform better than the MLR model.

Keywords Artificial neural networks · Asi River · Multiple linear regression · Relative importance · Water quality

✉ Mohammad Ali Ghorbani
ghorbani@tabrizu.ac.ir; m_Ali_ghorbani@ymail.com

Mohammad Taghi Aalami
Mtaalami@tabrizu.ac.ir

Leila Naghipour
Naghipour.L@tabrizu.ac.ir

1 Department of Water Engineering, Tabriz University, Tabriz, Iran

2 Department of Civil Engineering, Tabriz University, Tabriz, Iran

Introduction

Water quality is an explanation of chemical, physical, and biological characteristics of water in relation with intended use(s) and a set of standards (Gazzaz et al. 2012). Water quality can be evaluated by a single parameter such as electrical conductivity (EC) or by a number of critical parameters (e.g., temperature, pH, EC, turbidity; pathogens, nutrients, organics, and metals) for certain objective. The EC is a measurable quantity but their direct measurements are expensive, time-consuming and expensive. Artificial neural networks (ANNs) have been applied widely to time series analyses, including local water quality parameters and EC values, in which the model is developed even in the presence of correlation among the variables. ANN is nonlinear, non-parametric model and does not need necessarily higher physical meaning background of the subject. The initial model derived from data is a neural network model that can be built and handled quite easily and quickly. A disadvantage of ANNs is that they are black box models unable to provide any insight into the key relationships. Since statistical regression is the simplest and most straightforward form of a model, it is usually the first approach that is adopted for investigating a relationship between variables. Therefore, MLR was investigated as possible alternative, and its prediction abilities were compared with ANN models. Predictions by the MLR are simply based on linear and additive associations of the explanatory variables, and these models are not able to incorporate the nonlinearities of the parameters. Finally, the importance of each of the input parameters is estimated by a technique given by Garson (1991), which employs the weights between the artificial neurons produced by the ANN model. Several studies reported the use of ANN in water quality prediction (Liong et al. 1999; Diamantopoulou et al. 2005; Sahoo et al. 2005; Recknagel et al. 2007; El-Shafie et al. 2008; Amiri and Nakane 2009; Bertini et al. 2010; Maier et al. 2010; Sivapragasam et al. 2010; Pai et al. 2011; Ghorbani et al. 2012; Najad et al. 2013; Nemati et al. 2015).

The main purpose of this study is to investigate the applicability ANN methods to estimate the EC, and the results are compared with MLR. From 11 input candidates, pH, temperature, water discharge, sodium, and sum of calcium and magnesium concentrations, for a set of recorded data from 1984 to 2008 in the Asi River (also referred to as Orontes River), were used as input parameters to predict EC. Among water quality parameters, EC concentration is very important in classifying irrigation water (Singh et al. 2005). The paper also estimates the relative importance of these input variables.

Materials and methods

Multiple linear regression (MLR)

Multiple linear regression (MLR) is a conventional approach in the modeling of the relationship between variables in which the unknown parameters of the regression model are estimated. MLR fits a linear combination of the components of a multiple signal x to a single output signal y, as defined by (1) and returns the residual, r, i.e., the difference signal, as defined by (2):

$$y = a_0 + \sum_{i=1}^{n} a_i x_i \tag{1}$$

$$r = y - a_1x_1 - a_2x_2 - \cdots - a_nx_n - a_0 \tag{2}$$

where the values of parameters a_i are unknown a priori and, in this study, they are determined using the least squares method to minimize the residual errors, r.

Artificial neural networks (ANNs)

Artificial neural network is a nonlinear black box model and is a powerful tool for nonlinear problems. The feed-forward neural network (FFNN) is the widely used neural network architecture in literature and comprises a system of neurons, which are arranged in layers. Between the input and output layers, there may be one or more hidden layers. The number of neurons in the input and output layers is equal to the number of input and output variables, but the number of hidden layers and neurons in hidden layer are determined by trial-and-error method. Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to neurons in the next layer. These are summed to produce a net value, which is then transformed to an output value upon the application of an activation function. Figure 1 represents a three layers structure (MLP) that consists of (i) input layer, (ii) hidden layer and (iii) output layer. For more information, see (Nemati et al. 2015).

Relative importance index

Relative importance values and the saliency analysis are two of the approaches to open up the black box of the weights associated with the ANN models to gain some insight into the physical conditions of the site. This paper uses the relative importance method of the input variables, as given by the Garson equation (1991). It is based on the neural net weight matrix. Garson proposed following equation based on the partitioning of connection weights:

$$I_j = \frac{\sum_{m=1}^{m=N_\mathrm{h}} \left(\left(\frac{W_{jm}^{\mathrm{ih}}}{\sum_{k=1}^{k=N_\mathrm{i}} \left| W_{km}^{\mathrm{ih}} \right|} \right) \times \left| W_{mn}^{\mathrm{ho}} \right| \right)}{\sum_{k=1}^{k=N_\mathrm{i}} \left\{ \sum_{m=1}^{m=N_\mathrm{h}} \left(\left| W_{km}^{\mathrm{ih}} \right| / \sum_{k=1}^{k=N_\mathrm{i}} \left| W_{km}^{\mathrm{ih}} \right| \right) \times \left| W_{mn}^{\mathrm{ho}} \right| \right\}} \tag{3}$$

where I_j is the relative importance of the jth input variable on the output variable, N_i and N_h are the number of input and hidden neurons, respectively, and W is the connection weight, the superscripts i, h and o refer to input, hidden and

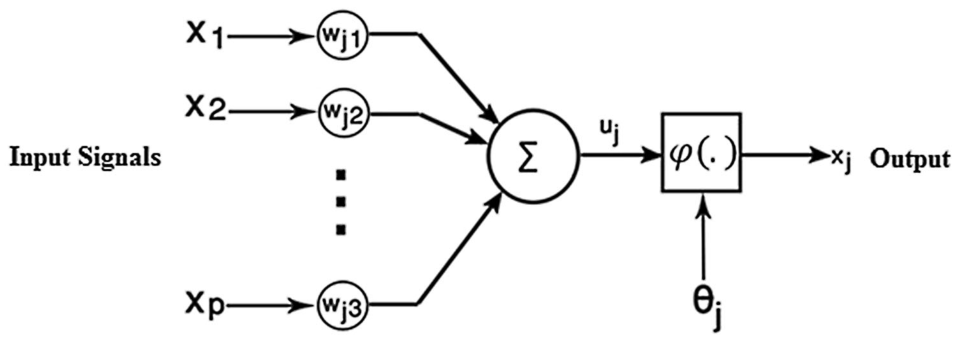

Fig. 1 Simple configuration of multilayer perceptron neural network (Nemati et al. 2015)

output layers, respectively, and subscripts k, m and n to input, hidden and output neurons, respectively. For more details, see (Ghorbani et al. 2012). The disadvantage of this method is that the network is not retrained after the removal of each input. This can lead to erroneous results if zero is not a reasonable value for the input. The result can be particulary questionable if the inputs are statistically dependent, because in general, the effects of different inputs cannot be separated (Chen et al. 2009).

Model performance evaluation

Four performance criteria are used in this study to assess the goodness of fit of the models, which are: root mean square error (RMSE), mean absolute error (MAE), mean square relative error (MSRE), and coefficient of determination (R^2) (further discussed by Ghorbani et al. 2012).

Study area and data specification

The investigation on EC in this paper is based on water quality parameters of one gauging station in Asi River. This river is international river; for this purpose, it has been divided into three basin districts, which originate in Lebanon in the Hermel Hills, cross Syria and end in Turkey. The location of this river is illustrated in Fig. 2.

The Asi River Basin, which was used to develop the model, is in southern Turkey in Antakya. Every month, samples were collected from one location, from the steel bridge station in Asi River, Turkey, for analysis which was located between latitude, 36°15′05″ North, longitude, 36°21′12″ East, and elevation 67 m.

From 11 input candidates, the most important and selected input variables were pH, temperature, water discharge, sodium, and sum of calcium and magnesium. The models were then used to predict EC. Concentrations of these parameters have been measured in 270 streams of Asi River at the steel bridge station in Antakya, Turkey, and on a monthly basis for the period of 24 years, from 1984 to 2008. The mean variations of EC and the other parameters of the gauging site used in this study are monthly intervals are shown in Fig. 3a–f, which also displays the missing data. The data are divided into two sets: (i) 80 % of data (216 months) for training the models; (ii) 20 % of data (54 months) for testing the models.

The statistical parameters of the water quality data are given in Table 1. The mean, minimum, maximum, standard deviation (Std Dev), variance (Var), skewness (Skew) and kurtosis can describe variability of the data. As described in Table 1, water temperature is one of the water quality variables that have a low skewness coefficient. Water discharge has a large skewness coefficient; the

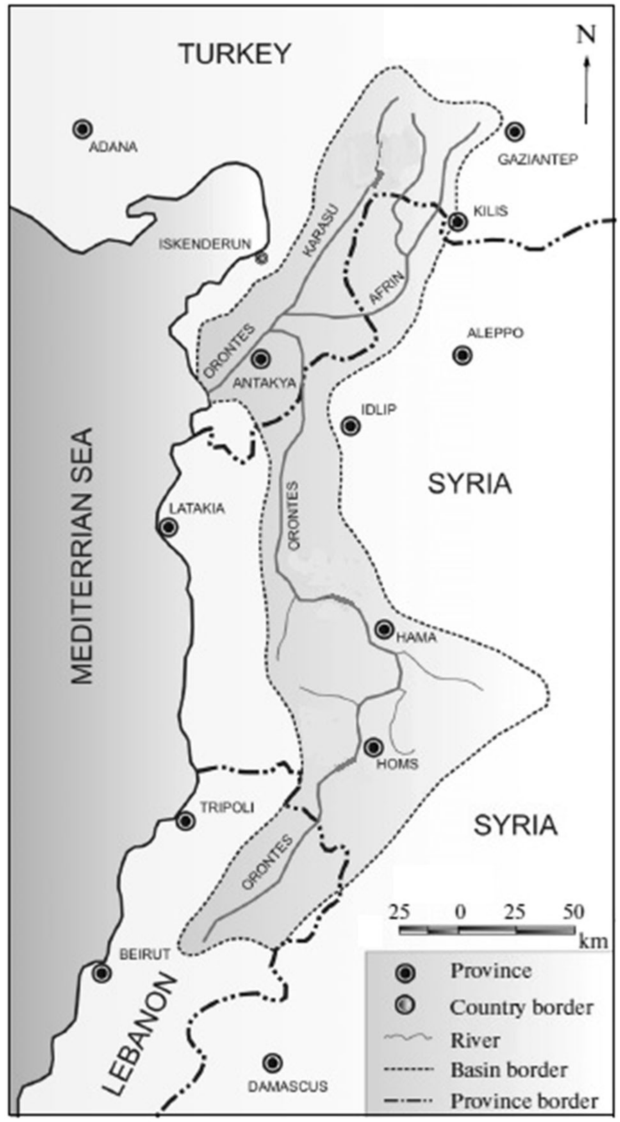

Fig. 2 Location of the Asi River

minimum and maximum values of the EC have large differences. Probably, the mean of the EC data set is heavily influenced by the presence of a few extreme values.

The data subsets were normalized so that the data rage fell between −1 and 1. Such scaling of data smooths the solution space and averages out some of the noise (ASCE 2000). Since results from these normalized models indicated that performance of the models did not change very much, the results here are represented without normalized data. The available records of monthly water quality parameters of Asi River at the steel bridge station suffer additionally from missing data. Some of appropriate strategies to treat the missing data are used (Honaker and King 2010).

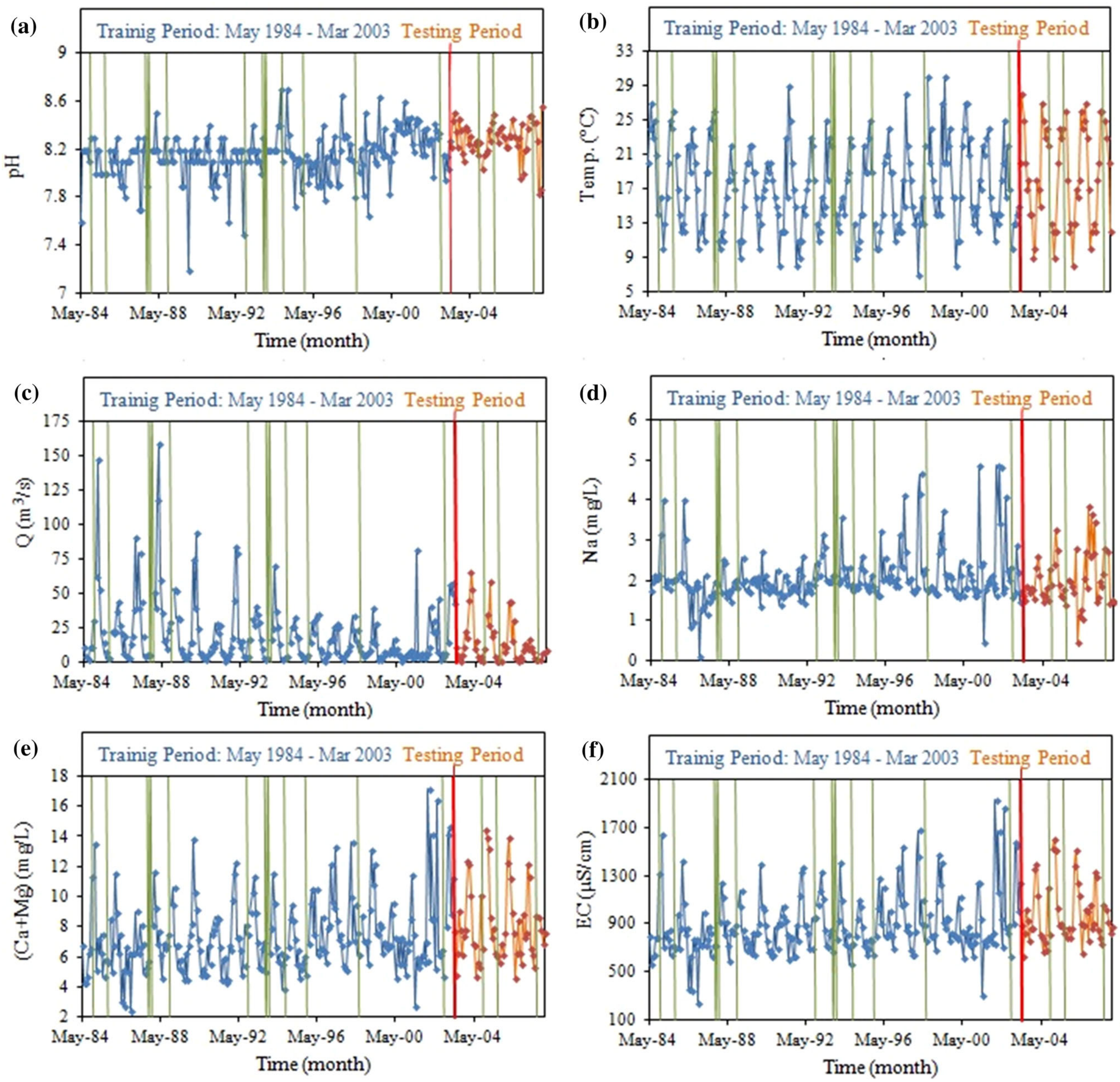

Fig. 3 Measured monthly time series of the water quality parameters at the Asi River: **a** temperature (temp, °C), **b** pH, **c** water discharge (Q, m^3/s), **d** sodium (Na, mg/L), **e** calcium and magnesium (Ca + Mg, mg/L), **f** electrical conductivity (EC, μS/cm)

Results

A typical feed-forward neural network of multilayer perceptrons model has been constructed for predicting the monthly EC time series. Table 2 shows the best values of the calibrating parameters for the ANNs. These parameters were fixed for all runs.

Relative importance

In this study, to determine the relative importance of temperature (Temp), pH, water discharge (Q), sodium (Na), and calcium and magnesium (Ca + Mg) concentration on EC, the Garson equation (6) was used. The ANN model architecture refers to the layout of neurons and the number of hidden layers, as shown in Fig. 1. Table 3 shows the results of ANN model for the training and testing periods.

In the testing phase, the model with 13 neurons for the hidden layer rendered comparatively better values of RMSE, MAE, MSRE, and R^2 (60.825 μS/cm, 45.639 μS/cm, 0.0033, and 0.952, respectively). Table 4 shows the matrices of weights between input, hidden and output layers.

Table 1 Statistics for water quality parameters of Asi River at the steel bridge station, period 1984–2008

Data	Unit		Mean	Min	Max	Std Dev	Var	Skew	Kurtosis
Input									
pH	–	Total	8.18	7.20	8.70	0.20	0.04	−0.77	2.58
		Training	8.15	7.20	8.70	0.20	0.04	−0.72	2.91
		Testing	8.28	7.84	8.56	0.15	0.02	−0.84	1.03
Temp	°C	Total	17.38	7	30	5.18	26.82	0.25	−0.84
		Training	17.13	7	30	4.98	24.77	0.32	−0.64
		Testing	18.37	8	28	5.86	34.39	−0.08	−1.29
Q	m^3/s	Total	18.73	0.30	158.56	22.46	504.56	2.78	10.79
		Training	19.96	0.94	158.56	23.72	562.60	2.75	10.17
		Testing	13.79	0.30	65.42	15.74	247.61	1.76	2.53
Na	mg/L	Total	2.07	0.10	4.86	0.66	0.43	1.68	4.89
		Training	2.09	0.10	4.86	0.66	0.43	1.93	5.94
		Testing	2.02	0.47	3.86	0.67	0.44	0.75	0.74
Ca + Mg	mg/L	Total	7.50	2.40	17.12	2.50	6.24	1.15	1.45
		Training	7.33	2.40	17.12	2.46	6.05	1.24	2.01
		Testing	8.16	4.55	14.45	2.56	6.54	0.94	0.05
Output									
EC	(µS/cm)	Total	907.46	246	1926	258.53	66,835.55	1.19	1.89
		Training	888.59	246	1926	258.85	67,005.33	1.30	2.51
		Testing	982.93	637	1605	245.26	60,153.81	1.00	0.15

Table 2 Initial parameter setting for implementing the ANN models

General setting	
Max epoch	100
Training algorithm	TRAINLM
Transfer function	TANSIG
Performance function	MSE
Adaption learning function	LEARNGDM

Table 5 shows relative importance of the input variables on EC, and indicates that (Ca + Mg), Q and pH play the most significant role on the EC model (with relative importance of 24.46, 21.97, and 19.67 %, respectively), whereas Na and temperature have less influential role (with relative importance of 18.10 and 15.84 %, respectively).

Input combinations

The relative importance of the input variables were used to determine appropriate input combinations. Different combinations of variables (Temp, pH, Q, Na, Ca + Mg) as input data, and EC as output of models were presented in Table 6.

MLR model

The standard form of the MLR model based on Eq. (1) is used for predicting EC, which included only the first order of the independent variables pH, Temp, Q, Na, and Ca + Mg. Table 7 presents the performance of the MLR model, and Fig. 4 illustrates the visual comparison between the observed and predicted values of EC for a typical data range of 270 data points. Comparison of the results in the training and testing steps indicated that combination 8 is the best of EC prediction for MLR model.

ANN model

In the preliminary investigations, the architecture of the ANN model was identified by trial-and-error procedure. A three-layer network was selected, and the number of neurons in the hidden layer was determined by training and testing four models: M1, M2, M3, and M4. The study tested the following recommendations: model M1 with I neurons as recommended by Tang and Fishwick (1993), model M2 with 2I as recommended by Wong (1992), and model M3 with 2I + 1 as recommended by Lippmann (1987), where I is the number of input variables, and model

Table 3 The results of ANN model for the training and testing periods to the identification of the number of the hidden layer neurons

Hidden layer neurons	Training				Testing			
	RMSE (μS/cm)	MAE (μS/cm)	MSRE	R^2	RMSE (μS/cm)	MAE (μS/cm)	MSRE	R^2
1	38.696	26.579	0.0058	0.978	62.132	45.758	0.0036	0.946
2	38.292	26.453	0.0041	0.979	75.490	54.853	0.0051	0.921
3	29.268	21.986	0.0016	0.987	66.704	49. 399	0.0044	0.937
4	29.704	21.797	0.0014	0.988	85.510	57.912	0.0056	0.905
5	32.545	22.587	0.0027	0.984	68.303	49.710	0.0046	0.935
6	163.452	47.468	0.0383	0.716	66.336	51.863	0.0039	0.952
7	33.454	22.306	0.0022	0.983	83.034	58.628	0.0057	0.906
8	34.270	24.051	0.0018	0.983	80.409	55.735	0.0052	0.915
9	23.118	18.334	0.0008	0.992	83.530	58.452	0.0072	0.914
10	29.332	22.126	0.0017	0.988	75.700	54.671	0.0053	0.921
11	31.489	23.395	0.0023	0.986	84.699	61.667	0.0061	0.911
12	36.626	23.874	0.0021	0.980	90.958	69.391	0.0078	0.873
13	**28.807**	**21.469**	**0.0012**	**0.988**	**60.825**	**45.639**	**0.0033**	**0.952**
14	32.265	22.600	0.0014	0.985	89.837	63.844	0.0077	0.888
15	35.851	19.583	0.0013	0.982	90.969	64.190	0.0072	0.874
16	28.891	18.690	0.0011	0.988	80.396	59.224	0.0058	0.908
17	57.688	26.623	0.0054	0.953	78.237	55.822	0.0051	0.919
18	34.488	26.294	0.0026	0.983	68.989	50.402	0.0051	0.927
19	25.498	19.858	0.0010	0.990	79.470	59.119	0.0059	0.909
20	30.914	19.384	0.0011	0.986	81.945	64.283	0.0067	0.904

The results in bold show the selected model

Table 4 Matrices of weights—w_1 weights between input and hidden layers, w_2 weights between hidden and output layers

w_1						w_2	
Neuron	Variable					Neuron	Variable
	pH	Temp (°C)	Q (m^3/s)	Na (mg/L)	(Ca + Mg) (mg/L)		EC (μS/cm)
1	0.1995	−0.0012	0.1373	0.9275	1.4209	1	1.3768
2	1.1907	−0.0030	1.6103	0.7860	−0.9184	2	−0.0760
3	2.2265	−2.3097	−3.9405	−0.5259	2.2975	3	0.0198
4	2.5658	0.3476	1.6094	4.4894	−1.2315	4	−0.0619
5	0.0722	0.1275	0.2014	0.3744	0.7229	5	1.5538
6	0.2507	−0.7097	3.4621	0.6780	2.5418	6	−0.7088
7	4.2985	−3.8656	2.4133	−1.9773	0.2988	7	−0.0428
8	0.2527	5.4694	−1.0241	−0.6271	2.1764	8	0.0067
9	0.4967	−4.2698	3.7799	−0.2198	2.3331	9	0.0343
10	−4.4561	−0.0964	−0.7138	−1.8480	−2.1113	10	−0.0603
11	3.8906	3.3156	4.6930	0.7586	−2.6389	11	−0.0506
12	−1.3637	0.3360	0.6167	5.3232	3.7807	12	−0.0539
13	3.7444	1.1158	−2.4746	−0.4803	−1.0091	13	−0.0141

M4 with 13 neurons. The ANN was compared based upon their prediction accuracy to identify the most appropriate and efficient combinations of inputs. The results showed that the network geometry with seven hidden neurons is required for a relatively better performance. This is shown in Fig. 5.

Table 8 shows the assessment of performance of the ANN model for the training and testing steps with

Table 5 Relative importance of input variables on EC

Input variables	Importance (%)
(Ca + Mg) (mg/L)	24.46
Q (m^3/s)	21.97
pH	19.67
Na (mg/L)	18.10
Temp (°C)	15.84
Total	100

different combinations of input parameters and structure. Among the models assessed, combination 1 with seven hidden neurons resulted in relatively better statistical measures. The visual comparison of predicted and observed EC values indicates that the ANN was able to properly model the variation of the EC parameter. However, some of the extreme values of EC have been underestimated or overestimated by the ANN model showing its relative weakness in the estimation of EC values (Fig. 6).

Based on the visual comparison, no substantial difference appears to be observed among the predictive abilities of the proposed models, and the predicted results for EC are just as good as those by MLR as shown in Fig. 4. The overall performance of the MLR and ANN techniques are presented in Table 9. It is clearly that the ANN model performed better than the MLR model.

Discussion

Prediction models are considered useful for river basin management and are used to predict the behavior of water quality with respect to changes in hydrological conditions. Neural networks have gained great popularity in time series prediction because of their robustness and simplicity with respect to underlying data distributions.

Asi River during its course receives varying levels of pollution from many diffuse (non-point) and point sources. This river is intensively used for agriculture owing to the existence of very fertile soil around the river, contributing significantly to the regional economy, so it is degraded by diffuse sources. In addition, nearly 200 industrial plants and hundreds of small factories are located around or nearby the river and discharge their effluents into the river at a rate of 500,000 m^3/year (Karakilcik and Erkul 2002), thus exhibiting large variations in water quality variables. On the other hand, measuring pH in the Asi River Basin for the past 24 years has shown that conditions of this river have also changed.

Water quality data for this analysis were limited to concentrations of sodium, potassium, calcium, magnesium, carbonate, chlorate, sulfate, bicarbonate as well as temperature, pH, and water discharge. Since, one of the most important steps in the development process of a model is the determination of an appropriate set of inputs, but on the other hand, inclusion of more inputs to the system increases system complexity, the input variables were selected and

Table 6 Combinations investigated for predicting monthly EC time series

Model	Input	Output
1	$(\mathrm{pH})_t$, $(Q)_t$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
2	$(\mathrm{pH})_t$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
3	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
4	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(Q)_t$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
5	$(\mathrm{pH})_t$, $(Q)_t$, $(\mathrm{Ca+Mg})_t$, $(\mathrm{EC})_{t-1}$	$(\mathrm{EC})_t$
6	$(\mathrm{pH})_t$, $(Q)_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
7	$(\mathrm{pH})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
8	$(\mathrm{pH})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$, $(\mathrm{EC})_{t-1}$	$(\mathrm{EC})_t$
9	$(\mathrm{pH})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$, $(\mathrm{EC})_{t-2}$, $(\mathrm{EC})_{t-1}$	$(\mathrm{EC})_t$
10	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(Q)_t$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
11	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(\mathrm{Na})_{t-1}$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
12	$(\mathrm{pH})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Na})_{t-1}$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
13	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(\mathrm{Na})_{t-1}$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$, $(\mathrm{EC})_{t-1}$	$(\mathrm{EC})_t$
14	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Na})_{t-1}$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$	$(\mathrm{EC})_t$
15	$(\mathrm{pH})_t$, $(\mathrm{Temp})_t$, $(Q)_{t-1}$, $(Q)_t$, $(\mathrm{Na})_{t-1}$, $(\mathrm{Na})_t$, $(\mathrm{Ca+Mg})_{t-1}$, $(\mathrm{Ca+Mg})_t$, $(\mathrm{EC})_{t-1}$	$(\mathrm{EC})_t$

Table 7 The results of MLR model for the training and testing periods

Combination	Training				Testing			
	RMSE (µS/cm)	MAE (µS/cm)	MSRE	R^2	RMSE (µS/cm)	MAE (µS/cm)	MSRE	R^2
1	50.245	36.077	0.0040	0.962	52.019	39.017	0.0028	0.963
2	29.549	21.881	0.0012	0.987	63.544	45.571	0.0035	0.945
3	29.467	21.652	0.0012	0.987	65.339	47. 332	0.0037	0.943
4	29.315	21.422	0.0012	0.987	66.512	48.231	0.0039	0.942
5	234.875	164.986	0.1045	0.176	217.657	159.831	0.0367	0.238
6	50.245	36.082	0.0040	0.962	52.355	39.204	0.0029	0.963
7	50.242	36.094	0.0040	0.962	52.412	39.276	0.0029	0.963
8	**49.321**	**35.077**	**0.0043**	**0.964**	**49.740**	**36.175**	**0.0026**	**0.964**
9	231.092	160.391	0.1056	0.196	219.851	161.251	0.0369	0.256
10	29.228	21.473	0.0012	0.987	67.579	48.620	0.0040	0.942
11	29.385	21.741	0.0012	0.987	65.953	47.551	0.0038	0.943
12	29.209	21.583	0.0012	0.987	67.626	48.780	0.0040	0.942
13	28.215	20.515	0.0012	0.988	58.394	40.672	0.0029	0.950
14	29.208	21.565	0.0012	0.987	67.745	48.903	0.0040	0.942
15	28.031	20.383	0.0012	0.988	57.275	39.237	0.0028	0.955

The results in bold show the selected model

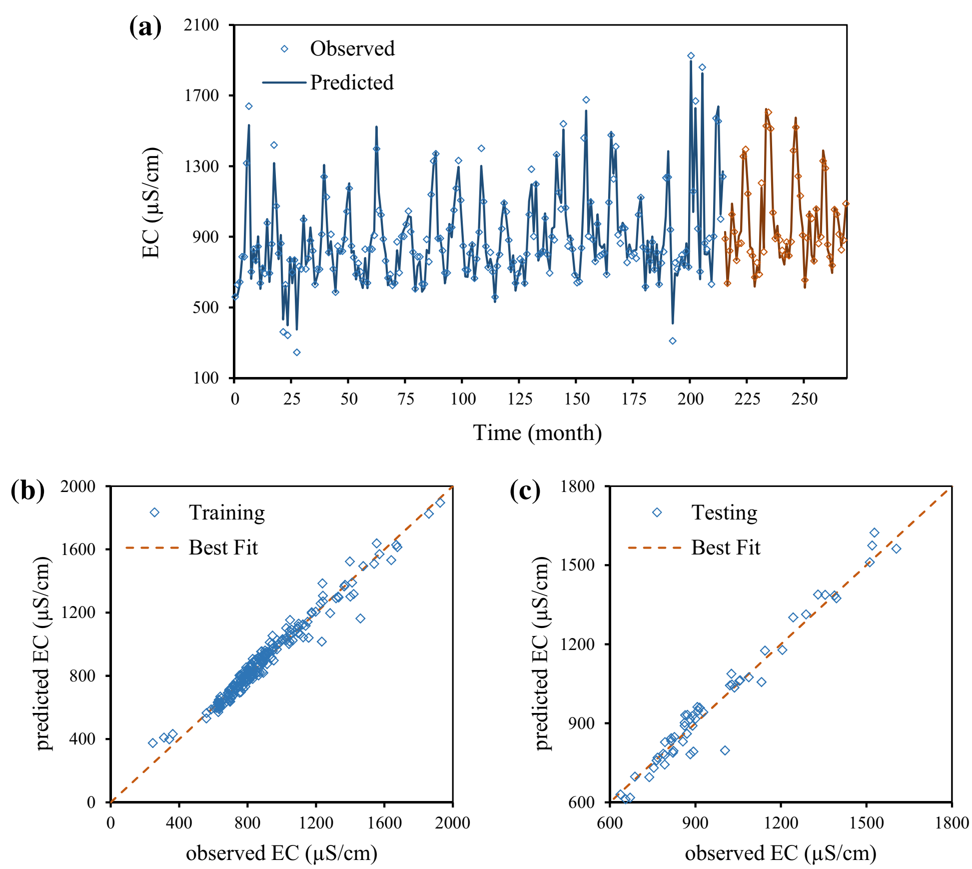

Fig. 4 Comparison of predicted MLR time series with observed values for EC: **a** sequence plot, **b** scatter plot for the training dataset, **c** scatter plot for the testing dataset

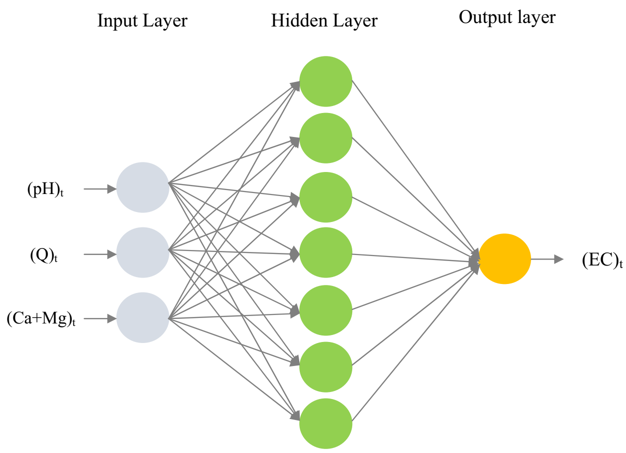

Fig. 5 Implementation of the ANN model

generated from the system description through literature experience.

In this study, the ANN modeling technique was used to predict future conditions in this river using pH, temperature, water discharge, sodium, sum of calcium and magnesium concentrations. The study also includes an estimation of the relative importance of these variables to identify important variables affecting the EC parameter. MLR is investigated as possible alternative and its prediction abilities were compared with ANNs.

Comparison between the models indicated that the interaction input with delay time is no more responsible for EC estimation than the individual variables, so increasing the amount of memory was not found to be a significant explanatory variable. The modeling results also indicated that

Table 8 The results of ANN model for the training and testing periods

Model	Combination	ANN structure	Training				Testing			
			RMSE (µS/cm)	MAE (µS/cm)	MSRE	R^2	RMSE (µS/cm)	MAE (µS/cm)	MSRE	R^2
M1	1	3–3–1	54.233	37.038	0.0078	0.956	52.884	39.096	0.0027	0.964
	2	3–3–1	29.032	21.906	0.0011	0.987	53.567	38.685	0.0028	0.957
	3	4–4–1	31.250	22.530	0.0013	0.986	79.776	57.930	0.0051	0.921
	4	5–5–1	29.529	20.874	0.0017	0.987	79.968	58.917	0.0059	0.916
	5	4–4–1	226.569	158.135	0.0990	0.237	239.501	189.308	0.0503	0.106
	6	4–4–1	53.519	36.224	0.0079	0.957	54.015	40.377	0.0030	0.964
	7	5–5–1	61.070	40.172	0.0130	0.951	54.629	40.295	0.0029	0.956
	8	6–6–1	54.917	37.448	0.0075	0.958	58.988	44.082	0.0036	0.958
	9	7–7–1	218.862	149.392	0.1015	0.280	224.605	172.649	0.0403	0.205
	10	6–6–1	26.311	18.850	0.0027	0.990	79.588	59.155	0.0054	0.928
	11	6–6–1	31.862	24.153	0.0025	0.986	63.616	48.868	0.0037	0.954
	12	7–7–1	25.239	19.811	0.0010	0.990	60.499	45.853	0.0035	0.957
	13	7–7–1	27.662	19.236	0.0009	0.989	68.463	43.999	0.0037	0.947
	14	8–8–1	26.819	19.550	0.0017	0.989	70.771	50.782	0.0044	0.937
	15	9–9–1	29.014	19.508	0.0009	0.988	75.386	53.129	0.0048	0.906
M2	1	3–6–1	47.735	32.915	0.0033	0.966	61.648	45.878	0.0032	0.965
	2	3–6–1	28.388	21.306	0.0011	0.988	67.449	49.453	0.0045	0.935
	3	4–8–1	28.630	21.636	0.0012	0.988	73.525	56.551	0.0049	0.934
	4	5–10–1	28.412	20.283	0.0013	0.988	81.366	63.141	0.0061	0.911
	5	4–8–1	228.632	155.749	0.0891	0.227	231.697	168.142	0.0404	0.166
	6	4–8–1	45.090	30.965	0.0042	0.970	58.251	43.695	0.0040	0.962
	7	5–10–1	49.874	35.539	0.0108	0.963	58.883	43.238	0.0028	0.957
	8	6–12–1	48.184	31.168	0.0058	0.966	64.933	44.350	0.0038	0.941
	9	7–14–1	222.108	158.157	0.1005	0.266	230.857	170.797	0.0411	0.169
	10	6–12–1	36.933	26.210	0.0025	0.982	80.253	53.879	0.0050	0.914
	11	6–12–1	26.058	17.895	0.0009	0.990	89.945	65.723	0.0068	0.901
	12	7–14–1	46.308	24.902	0.0032	0.968	57.847	43.301	0.0031	0.957
	13	7–14–1	28.245	20.672	0.0010	0.988	56.532	39.782	0.0032	0.953
	14	8–16–1	28.738	20.921	0.0016	0.988	74.360	56.926	0.0056	0.938
	15	9–18–1	24.350	16.087	0.0009	0.991	70.105	51.684	0.0044	0.933

Table 8 continued

Model	Combination	ANN structure	Training				Testing			
			RMSE (μS/cm)	MAE (μS/cm)	MSRE	R^2	RMSE (μS/cm)	MAE (μS/cm)	MSRE	R^2
M3	1	3–7–1	**46.927**	**32.462**	**0.0029**	**0.968**	**50.810**	**37.495**	**0.0024**	**0.965**
	2	3–7–1	28.290	20.150	0.0010	0.988	68.804	51.447	0.0041	0.937
	3	4–9–1	35.554	23.422	0.0040	0.981	68.799	48.919	0.0050	0.924
	4	5–11–1	27.950	20.513	0.0011	0.988	85.786	65.313	0.0065	0.917
	5	4–9–1	215.918	154.270	0.0930	0.304	273.532	211.553	0.0623	0.002
	6	4–9–1	50.701	36.167	0.0070	0.963	52.710	40.295	0.0028	0.963
	7	5–11–1	59.052	39.978	0.0161	0.950	70.247	52.268	0.0041	0.946
	8	6–13–1	55.986	33.696	0.0104	0.955	55.217	40.659	0.0029	0.959
	9	7–15–1	216.991	151.167	0.1079	0.303	219.832	167.045	0.0434	0.235
	10	6–13–1	25.443	19.917	0.0010	0.990	60.022	45.372	0.0034	0.960
	11	6–13–1	29.708	23.050	0.0012	0.988	74.154	55.094	0.0058	0.923
	12	7–15–1	37.707	26.204	0.0020	0.979	90.157	63.413	0.0062	0.904
	13	7–15–1	30.814	22.108	0.0013	0.988	78.551	52.415	0.0046	0.924
	14	8–17–1	33.695	25.014	0.0020	0.984	70.503	51.086	0.0047	0.929
	15	9–19–1	32.288	22.608	0.0031	0.985	69.888	49.134	0.0040	0.927
M4	1	3–13–1	47.708	33.445	0.0062	0.968	54.089	42.375	0.0030	0.957
	2	3–13–1	26.739	20.477	0.0011	0.989	56.442	40.758	0.0031	0.950
	3	4–13–1	29.983	21.508	0.0014	0.986	64.433	45.708	0.0045	0.938
	4	5–13–1	26.724	20.227	0.0011	0.989	70.424	50.549	0.0045	0.925
	5	4–13–1	223.271	155.173	0.0872	0.256	260.513	196.732	0.0505	0.090
	6	4–13–1	43.473	29.601	0.0022	0.972	74.739	53.080	0.0050	0.929
	7	5–13–1	45.551	31.815	0.0027	0.970	72.960	55.703	0.0045	0.932
	8	6–13–1	55.986	33.696	0.0104	0.955	55.217	40.659	0.0029	0.959
	9	7–13–1	217.129	154.870	0.1092	0.311	212.224	168.452	0.0400	0.261
	10	6–13–1	25.443	19.917	0.0010	0.990	60.022	45.372	0.0034	0.960
	11	6–13–1	29.708	23.050	0.0012	0.988	74.154	55.094	0.0058	0.923
	12	7–13–1	21.227	15.425	0.0008	0.993	60.986	48.743	0.0036	0.954
	13	7–13–1	36.899	26.053	0.0038	0.982	56.947	43.573	0.0029	0.956
	14	8–13–1	31.250	21.056	0.0014	0.985	65.652	51.468	0.0046	0.944
	15	9–10–1	35.760	24.159	0.0019	0.982	80.522	57.109	0.0049	0.923

The results in bold show the selected model

similar performances were obtained with MLR and ANNs in the testing step, but better performance indices were achieved with ANN models in both steps, suggesting that it could be successfully applied for EC predicting. Despite the accuracy of MLR models being slightly lower than the ANN model, the MLR was superior to other artificial intelligence models in giving a simple equation for the phenomenon which shows the relationship between the input and output parameters. The ANN model can generate output values in continuous form, which makes water quality assessment more comprehensible, so this model was selected as the best fitting.

For the modeling and analysis of EC, only monthly data were available and used in this study, which might not be sufficient for accurate modeling and model assessment, for monthly data may not include all extreme conditions.

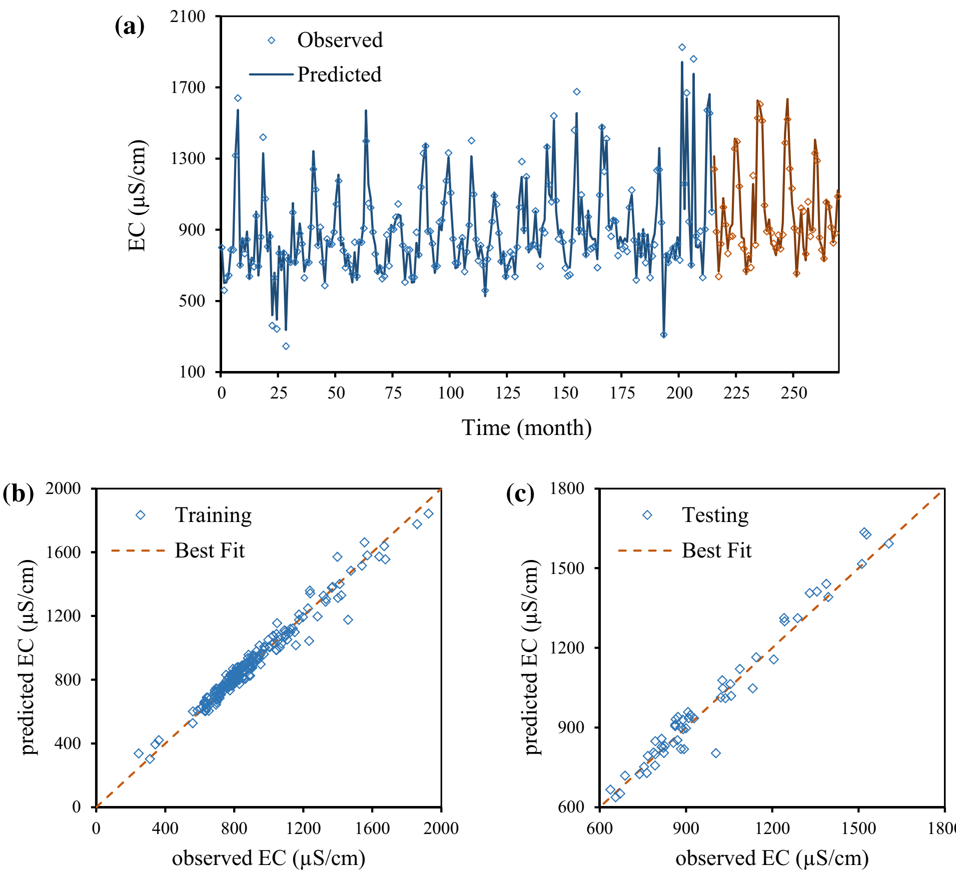

Fig. 6 Comparison of predicted ANN time series with observed values for EC: **a** sequence plot, **b** scatter plot for the training dataset, **c** scatter plot for the testing dataset

Table 9 Comparison of the performances of MLR and ANN models

	Model	
	MLR	ANN
RMSE (µS/cm)		
Training	49.321	46.927
Testing	49.740	50.810
MAE (µS/cm)		
Training	35.077	32.462
Testing	36.175	37.495
MRSE		
Training	0.0043	0.0029
Testing	0.0026	0.0024
R^2		
Training	0.964	0.968
Testing	0.964	0.965

Conclusion

The general objective of this study is to predict monthly EC time series using local water quality parameters of pH, temperature, water discharge, sodium, and sum of calcium and magnesium. The recorded data at one station located in Asi River, at a gauging site in Antakya, Turkey, are used to investigate the performance of two modeling strategies: ANNs, and MLR for the estimation of the EC amounts. This study also employs the Garson equation to assess the relative importance of these input variables. The modeling study employed different input combinations, and model performances have been estimated by means of several indicators. The results indicated that reasonable prediction accuracy was achieved for these models.

Acknowledgments The authors would like to acknowledge and thank Prof. Ozgur Kisi, from Keyseri University, Turkey, for providing the data used in this study. The authors would also like to express their gratitude to Dr. Michael S. Smith for his generous helps in editing this paper.

References

Amiri BJ, Nakane K (2009) Comparative prediction of stream water total nitrogen from land cover using artificial neural network and multiple linear regression approaches. Polish J Environ Stud 18(2):151–160

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000) Artificial neural networks in hydrology, I: preliminary concepts. J Hydrol Eng 5(2):115–123

Bertini I, Ceravolo F, Citterio M, Felice MD, Pietra BD, Margiotta F, Pizzuti S, Puglisi G (2010) Ambient temperature modeling with soft computing techniques. Sol Energy 84(7):1264–1272

Chen T, Zhang Ch, Chen X, Li L (2009) An input variable selection method for the artificial neural network of shear stiffness of worsted fabrics. Statistical analysis and data mining. ASA Data Sci J 1(5):287–295

Diamantopoulou MJ, Papamichail DM, Antonopoulos VZ (2005) The use of a neural network technique for the prediction of water quality parameters. Oper Res 5(1):115–125

El-Shafie A, Noureldim AE, Taha MR, Basri H (2008) Neural network model for Nile River inflow forecasting analysis of historical inflow data. J Appl Sci 8(24):4487–4499

Garson GD (1991) Interpreting neural-network connection weights. Artif Intell Expert 6:47–51

Gazzaz NM, Yusoff MK, Aris AZ, Juahir H, Ramli MF (2012) Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors. Mar Pollut Bull 64(11):2409–2420

Ghorbani MA, Khatibi R, Hosseini B, Bilgili M (2012) Relative importance of parameters affecting wind speed prediction using artificial neural networks. Theor Appl Climatol 110(4). doi:10.1007/s00704-012-0821-9

Honaker J, King G (2010) What to do about missing values in time series cross-section data. Am J Polit Sci 54(3):561–581

Karakilcik Y, Erkul H (2002) Management of Asi River. Detay, Turkey, p 356

Liong SY, Lim WH, Paudyal G (1999) Real time river stage forecasting for flood Bangladesh: neural network approach. J Comput Civil Eng 14(1):1–18

Lippmann RP (1987) An introduction to computing with neural nets. ASSP Mag IEEE 4(2):4–22

Maier HR, Jain A, Dandy GC, Sudheer KP (2010) Methods used for the development of neural networks for the prediction of water resource variables in river systems: current status and future directions. Environ Model Softw 25(8):891–909

Najad A, El-Shafie A, Karim OA, El-Shafie AH (2013) Application of artificial neural networks for water quality prediction. Neural Comput Appl 22(1):187–201

Nemati S, Fazelifard MH, Terzi O, Ghorbani MA (2015) Estimation of dissolved oxygen using data-driven techniquesin the Tai Po River. Environ Earth Sci, Hong Kong. doi:10.1007/s12665-015-4450-3

Pai TY, Yang PY, Wang SC, Lo MH, Chiang CF, Kuo JL, Chu HH, Su HC, Yu LF, Hu HC, Chang YH (2011) Predicting effluent from the wastewater treatment plant of industrial park based on fuzzy network and influent quality. Appl Math Model 35(8):3674–3684

Recknagel F, Chan WS, Cao H, Park HD (2007) Elucidation and short-term forecasting of microcystin concentrations in Lake Suwa (Japan) by means of artificial neural networks and evolutionary algorithms. Water Res 41(10):2247–2255

Sahoo GB, Ray C, Wang JZ, Hubbs SA, Song RG, Jasperse J, Seymour D (2005) Use of artificial neural networks to evaluate the effectiveness of riverbank filtration. Water Res 39(12):2505–2516

Singh AK, Mondal GC, Sing PK, Singh S, Singh TB, Tewary BK (2005) Hydrochemistry of reservoirs of Damodar river basin, India: weathering processes and water quality assessment. J Environ Geol 48:1014–1028

Sivapragasam C, Jegatheesan V, Arun VM, Vanitha S (2010) Spatial modeling of electrical conductivity with neural network. Int J Eng Sci Technol 2(7):3128–3136

Tang Z, Fishwick PA (1993) Feedforward neural nets as models for time series forecasting. ORSA J Comput 5(4):374–385

Wong FS (1992) Time series forecasting using back propagation neural network. Neurocomputing 2(4):147–159